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Research Article

Detection of Disturbances in Voltage Signals for Power Quality Analysis Using HOS

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This paper outlines a *higher-order statistics* (HOS)-based technique for detecting abnormal conditions in voltage signals. The main advantage introduced by the proposed technique refers to its capability to detect voltage disturbances and their start and end points in a frame whose length corresponds to, at least, $N = 16$ samples or 1/16 of the fundamental component if a sampling rate equal to $f_s = 256 \times 60$ Hz is considered. This feature allows the detection of disturbances in submultiples or multiples of one-cycle fundamental component if an appropriate sampling rate is considered. From the computational results, one can note that almost all abnormal and normal conditions are correctly detected if $N =$ s256, 128, 64, 32, and 16 and the SNR is higher than 25 dB. In addition, the proposed technique is compared to a *root mean square* (rms)-based technique, which was recently developed to detect the presence of some voltage events as well as their sources in a frame whose length ranges from 1/8 up to one-cycle fundamental component. The numerical results reveal that the proposed technique shows an improved performance when applied not only to synthetic data, but also to real one.

1. INTRODUCTION

The increasing pollution of power line signals and its impact on the quality of power delivery by electrical utilities to end users are pushing forward the development of signal processing tools to provide several functionalities, among them it is worth mentioning the following ones [1]: (i) disturbances detection, (ii) disturbances classification, (iii) disturbance sources identification, (iv) disturbance sources localization, (v) transients analysis, (vi) fundamental, harmonic, and interharmonic parameters estimations, (vii) disturbances compression, (viii) signal segmentation, and so forth.

Regarding the *power quality* (PQ) monitoring needs, one can note that the detection of disturbances as well as their start and end points in electric signals is a very important issue to upcoming generation of PQ monitoring equipment. In fact, the detection technique has to present good performance under different sampling rates, frame lengths ranging from submultiples up to multiples of power frequency cycle and varying *signal-to-noise ratio* (SNR) conditions. Therefore, for those interested in disturbance analysis, one of the first and most important function of a monitoring equipment is to provide a real-time and reliable detection of disturbances to facilitate their further characterization. In addition, the detection technique has to be capable of recognizing short-time and long-time disturbances with high detection rate.

Additionally, it is worth mentioning that PQ equipment for detecting events and variations has to activate the disturbance tracking so that the portion of the signal including the disturbance is the only segment processed. As a result, a reliable detection of disturbances as well as the their localizations in the power line signals facilitate the design and use of classification, compression, identification, signal representation, and parameters estimation to provide a comprehensive analysis of voltage disturbances.

The necessity of improved detection performance for continuous monitoring of electric signals has motivated the development of several techniques that show a good trade-off between computational complexity and performance [2–13]. In fact, the correct detection of disturbances in voltage signals as well as their start and end points can provide relevant information to characterize the PQ disturbances and, maybe, their sources.

In this regard, a great deal of attentions has been drawn toward wavelet transform-based technique for detection purpose. However, recent results have indicated that wavelet transform-based techniques are very sensitive to the presence high power background noise [14]. Another very interesting techniques are the ones that make use of second-order information of the error signal, which is the result of the subtraction of the fundamental component from the electric signal, for detection purpose. The analysis of the error signal is attractive and interesting solution to characterize the presence of disturbances as discussed in [2, 4, 5, 8]. Among these techniques, one can point out that the technique introduced in [2] is, at the first sight, a very interesting solution because it makes use of the innovation concept applied to the Kalman filtering formulation [15] and, as a consequence, it demands low computational cost and attains good performance if at least one-cycle fundamental component is considered.

The techniques proposed in [2, 4, 5, 8] are very similar in the sense that all of them make use of second-order statistics of the error signal to detect the occurrence of disturbances. Analyzing [2, 8], one notes that the advantage of the former technique resides on the fact that it is a more sophisticated technique than the latter one. However, it is worth mentioning that the second-order statistics are very sensitive to the presence of Gaussian noise that usually models the background noise in voltage signals [1, 2]. As a result, the use of such statistics could not be appropriate for those cases where the power of background noise is high. On the other hand, the use of higher-order statistics (HOS) such as cumulants is very interesting, because they are insensitive to the presence of Gaussian noise [16, 17].

This paper introduces a technique based on HOS having the following advantages: (i) it is more insensitive to the presence of background noise modeled as a Gaussian than previous techniques developed so far; (ii) it is capable of detecting the occurrence of disturbances in frames whose lengths correspond to at least $N = 16$ samples, independent of the choice of the sampling rate; and (iii) it pinpoints the start and end points of the detected events. As a result, the proposed technique could be used in noisy scenarios and situations where the detection of disturbances in frames whose lengths correspond to submultiples or multiples of one-cycle fundamental component is needed. Simulation results verify that the proposed technique is capable of providing improved detection rate when applied to synthetic and real data. This technique was partially introduced in [18].

The paper is organized as follows. Section 2 formulates the detection problem. Section 3 presents the proposed technique for disturbance detection. Section 4 presents some numerical results about the performance and applicability of the proposed technique. Finally, concluding remarks are stated in Section 5.

2. PROBLEM FORMULATION

The discrete version of monitored power line signals are divided into nonoverlapped frames of N samples and the discrete sequence in a frame can be expressed as an additive contribution of several types of phenomena

$$x(n) = x(t)|_{t=nT_s} := f(n) + h(n) + i(n) + t(n) + v(n), \tag{1}$$

where $n = 0, \dots, N-1$, $T_s = 1/f_s$ is the sampling period, the sequences $\{f(n)\}$, $\{h(n)\}$, $\{i(n)\}$, $\{t(n)\}$, and $\{v(n)\}$ denote the power supply signal (or fundamental component), harmonics, interharmonics, transient, and background noise, respectively. Each of these signals is defined as follows:

$$f(n) := A_0(n)\cos\left[2\pi\frac{f_0(n)}{f_s}n + \theta_0(n)\right], \tag{2}$$

$$h(n) := \sum_{m=1}^{M} h_m(n), \tag{3}$$

$$i(n) := \sum_{j=1}^{J} i_j(n), \tag{4}$$

$$t(n) := t_{\text{spi}}(n) + t_{\text{not}}(n) + t_{\text{cas}}(n) + t_{\text{dae}}(n), \tag{5}$$

and $v(n)$ is independently and identically distributed (i.i.d.) noise as normal $\mathcal{N}(0, \sigma_v^2)$ and independent of $\{f(n)\}$, $\{h(n)\}$, $\{i(n)\}$, and $\{t(n)\}$.

In (2), $A_0(n)$, $f_0(n)$, and $\theta_0(n)$ refer to the magnitude, fundamental frequency, and phase of the power supply signal, respectively. In (3), $h_m(n)$ and $i_j(n)$ are the mth harmonic and the jth interharmonic, respectively, which are defined as

$$h_m(n) := A_m(n)\cos\left[2\pi m\frac{f_0(n)}{f_s}n + \theta_m(n)\right], \tag{6}$$

$$i_j(n) := A_{I,j}(n)\cos\left[2\pi\frac{f_{I,j}(n)}{f_s}n + \theta_{I,j}(n)\right]. \tag{7}$$

In (6), $A_m(n)$ is the magnitude and $\theta_m(n)$ is the phase of the mth harmonic. In (7), $A_{I,j}(n)$, $f_{I,j}(n)$, and $\theta_{I,j}(n)$ are the magnitude, frequency, and phase of the jth interharmonic, respectively. In (5), $t_{\text{spi}}(n)$, $t_{\text{not}}(n)$, $t_{\text{dec}}(n)$, and $t_{\text{dam}}(n)$ represents transients named spikes, notches, decaying oscillations, and damped exponentials. These transients are expressed by

$$t_{\text{spi}}(n) := \sum_{i=1}^{N_{\text{spi}}} t_{\text{spi},i}(n), \tag{8}$$

$$t_{\text{not}}(n) := \sum_{i=1}^{N_{\text{not}}} t_{\text{not},i}(n), \tag{9}$$

$$\begin{aligned} t_{\text{dec}}(n) := \sum_{i=1}^{N_{\text{dec}}} & A_{\text{dec},i}(n)\cos\left[\omega_{\text{dec},i}(n)n + \theta_{\text{dec},i}(n)\right] \\ & \times \exp\left[-\alpha_{\text{dec},i}(n - n_{\text{dec},i})\right], \end{aligned} \tag{10}$$

$$t_{\text{dam}}(n) := \sum_{i=1}^{N_{\text{dam}}} A_{\text{dam},i}(n)\exp\left[-\alpha_{\text{dam},i}(n - n_{\text{dam},i})\right], \tag{11}$$

respectively, where $t_{\text{spi},i}(n)$ and $t_{\text{not},i}(n)$ are the nth samples of the ith transient named spike or notch. Note that (10) refers to the capacitor switchings as well as signals resulted from faulted waveforms. Equation (11) defines the decaying exponential as well as *direct current* (DC) components ($\alpha_{\text{dam}} = 0$) generated as a results of geomagnetic disturbances, and so forth.

The following definitions are used in this contribution: (i) the vector $\mathbf{x} = [x(n) \cdots x(n-N+1)]^T$ is composed of samples from the signal expressed by (1); (ii) the vector $\mathbf{f} = [f(n) \cdots f(n-N+1)]^T$ is constituted by estimated samples from the signal expressed by (2); (iii) the vector $\mathbf{v} = [v(n) \cdots v(n-N+1)]^T$ is the additive noise vector; and (iv) $\mathbf{u} = \mathbf{h}+\mathbf{i}+\mathbf{t} = [u(n) \cdots u(n-N+1)]^T$ is composed of the vectors formed by samples of the signals represented by (3)–(5).

The detection of disturbances in the vector $\mathbf{x}$ can be formulated as the decision between two hypotheses [19–21],

$$\begin{aligned}\mathcal{H}_0 &: \mathbf{x} = \mathbf{f}_{ss} + \mathbf{v},\\ \mathcal{H}_1 &: \mathbf{x} = \mathbf{f}_{ss} + \Delta\mathbf{f}_{ss} + \mathbf{u} + \mathbf{v},\end{aligned} \tag{12}$$

where hypothesis $\mathcal{H}_0$ refers to normal conditions of voltage signals and hypothesis $\mathcal{H}_1$ is related to abnormal conditions in voltage signals. In (12), the vector $\Delta\mathbf{f}_{ss}$ represents a sudden variation in the fundamental component and the vector $\mathbf{f}_{ss}$ denotes the steady-state component of the fundamental component. Finally, the vector $\mathbf{u}$ refers to the occurrence of disturbances in the voltage signals whose components do not appear in the fundamental component.

Supposing that L is the length of the disturbance and $N > L$, one can assume that $\mathbf{x} = \mathbf{f}_{ss} + \Delta\mathbf{f}_{ss} + \mathbf{u} + \mathbf{v} = [x(n) \cdots x(n-N+1)]^T$, $\mathbf{u}+\Delta\mathbf{f}_{ss} = [\mathbf{0}_d^T, (\mathbf{u}+\Delta\mathbf{f}_{ss})_L^T, \mathbf{0}_{N-L-d}^T]^T$, and $(\mathbf{u}+\Delta\mathbf{f}_{ss})_L = [u(n+d)+\Delta f_{ss}(n+d) \cdots u(n+d+L-1)+\Delta f_{ss}(n+d+L-1)]^T$ is the disturbance vector. $\mathbf{0}_m$ is a column vector with m elements equal to zero. d and $d+L$ are start and end points of the disturbance in the N-length frame. Based on this formulation, the disturbance occurrence interval is denoted by

$$\Psi(n) = \mu(n-d) - \mu(n-d-L), \tag{13}$$

where $\mu(n)$ is a unit step function.

The disturbance detection process involves several variables that depend on the kind of application. For instance, the starting point d could be known or not; the duration L could be available or not; the wave shape of the disturbance $(\mathbf{u}+\Delta\mathbf{f}_{ss})_L$ can be known, partially known, or completely unknown [19, 22, 23]. In this context, $\mathcal{H}_0$ is a simple hypothesis and $\mathcal{H}_1$ is a composite hypothesis.

From the detection theory, it is known that if the background noise $\mathbf{v}$ is additive, i.i.d., and its elements are Gaussian random variables with known parameters, then the *generalized likelihood ratio test* (GLRT) is the classical process which assumes the form of a matched filter [19–21, 24]. However, the evaluation of such technique demands high computational complexity. One can note that if the background noise $\mathbf{v}$ is not Gaussian, then the evaluation of the GLRT presents additional computational complexity even for off-line applications [19–22].

Analyzing the vector $\mathbf{v}$, one can note that this signal usually is modeled as an i.i.d. random process in which the elements present an Gaussian *probability density function* (p.d.f.). Therefore, the use of second-order statistics to analyze the occurrence of disturbances can severely degrade the detection performance if the power of $\mathbf{v}$ is high. Another very important concern resides on the fact that if the vector $\mathbf{v}$ neither is an i.i.d. random process nor a Gaussian one, then the use of second-order statistics can be very unreliable to extract qualitative information if the power of the Gaussian noise is high.

On the other hand, the use of *higher-order statistics* (HOS) based on cumulants seems to be a very promising approach for disturbance detection in voltage signals because they are more appropriate for dealing with Gaussian signals. In fact, the cumulants are blind to any kind of Gaussian process, whereas second-order information is not. Then, cumulant-based signal processing techniques can handle colored Gaussian noise automatically, whereas second-order techniques may not. Therefore, cumulant-based techniques boost signal-to-noise ratio when electric signals are corrupted by Gaussian noise [17].

Additionally, the higher-order-based cumulants provide more relevant information from the random process. The use of such relevant information for detection purpose and other applications such as parameters estimation and classification have been successfully investigated in several applications [16, 17, 23–25] which are not related to power systems. Based on this discussion and assuming that $\mathbf{v}$, $\mathbf{f}$, and $\mathbf{u}$ carry out relevant information from the disturbance occurrence, then the hypotheses stated in (12) are reformulated as follows:

$$\begin{aligned}\mathcal{H}_0 &: \mathbf{u} = \mathbf{v}_u,\\ \mathcal{H}_1 &: \mathbf{f} = \mathbf{f}_{ss} + \mathbf{v}_f,\\ \mathcal{H}_2 &: \mathbf{u} = \mathbf{h} + \mathbf{i} + \mathbf{t} + \mathbf{v}_u,\\ \mathcal{H}_3 &: \mathbf{f} = \mathbf{f}_{ss} + \Delta\mathbf{f}_{ss} + \mathbf{v}_f,\end{aligned} \tag{14}$$

where $\mathbf{v} = \mathbf{v}_u + \mathbf{v}_f$. The hypotheses formulation introduced in (14) emphasizes the need to analyze abnormal events through the so-called *primitive* components of voltage signals that are represented by the vectors $\mathbf{f}$ and $\mathbf{u}$. While the hypotheses $\mathcal{H}_0$ and $\mathcal{H}_1$ are related to normal conditions of such voltage signal components, the hypotheses $\mathcal{H}_2$ and $\mathcal{H}_3$ are associated with abnormal conditions in these components.

Equation (14) means that we are looking for some kind of abnormal behavior in one or two *primitive components* of $\mathbf{x}$ so that a decision about disturbance occurrences is accomplished. This concept is very attractive, because the vectors $\mathbf{f}_{ss}+\Delta\mathbf{f}_{ss}+\mathbf{v}_f$ and $\mathbf{h}+\mathbf{i}+\mathbf{t}+\mathbf{v}_u$ can reveal insightful and different information from the voltage signals. These information not only leads to efficient and simple detection technique, but also contribute to the development of very promising compression, classification, and identification techniques for PQ applications [1].

In Section 3, the high-order statistics-based technique that implements (14) to detect abnormal events as well as their start and end points in frame composed of a reduced number of samples is introduced.

3. PROPOSED TECHNIQUE

As far as disturbance detection is concerned, an important issue that have come to our attention is the fact that all detection techniques presented so far do not address the problem of the minimum number of samples, $N_{\min}$, needed to detect with high performance the occurrence of disturbances. In fact, the development of techniques based on this premise is interesting in the sense that for a given $N_{\min}$, it is possible to design a detection technique capable of achieving a high detection rate independent of the sampling rate, f_s.

Then, by using an appropriate sampling rate, it will be possible to detect disturbances in frames whose lengths correspond to multiples or submultiples of one-cycle fundamental component. The detection technique proposed in [3] is the only one that tried to detect a reduced set of disturbances as well as their correspondence to disturbance sources in frames whose lengths range from 1/8 up to one-cycle fundamental component. And, as very well reported, it is an interesting technique to the set of selected disturbances considered in [3]. However, this technique could not be an attractive if the disturbance set is comprised of a large number of disturbances. The numerical results, which are obtained with synthetic and real voltage waveforms and are reported in Section 4, are in support of this statement. One has to note that our statement, by no means, invalidate the applicability of this technique for its intentional use as addressed in [3]. In fact, we are just attempting to highlight the fact that the only one technique introduced so far to identify disturbance source from the detected disturbances in submultiples of one cycle of the fundamental component is the only available technique that could be considered for comparison with the proposed technique.

We call attention to the fact that the technique discussed in this section allows detection rates very close to 100% if SNR is higher than 25 dB and the number of samples in the vector $\mathbf{x}$ is higher than 16, see simulation results in Section 4. As a result, the proposed technique can be applied to detect a large number of disturbances ranging from variations to high-frequency content events if an appropriate sampling rate is taken into account. For example, if $f_s = 32 \times 60$ Hz, then the proposed technique provides a high detection rate when the frame is composed of at least 16 samples, which correspond to a half-cycle fundamental component. In the case of $f_s = 512 \times 60$ Hz, similar detection rate is attained in a frame whose length corresponds to at least 1/32 cycles of the fundamental component. One can note that if this technique is well designed to a target sampling rate, then it will be capable of detecting disturbances in a very short-time interval corresponding to submultiples of one cycle of the fundamental component.

The disturbance detection in a frame whose length corresponds to more than one-cycle fundamental component is not a novelty. In fact, the novelty is the high detection rate attained when the frame lengths correspond to submultiples of one-cycle fundamental component, which is offered by the proposed technique. Note that the detection capacity of this technique is improved if the frame lengths corresponding to more than one cycle of the fundamental component are used because the use of a large number of samples allows a better estimation of the HOS-based parameters. By using the proposed technique, one is able to design source identification and disturbance classification techniques that can use the transient behavior associated with the detected disturbances to classify the disturbances and to identify the possible disturbance sources for the ongoing disturbance in a short-time intervals.

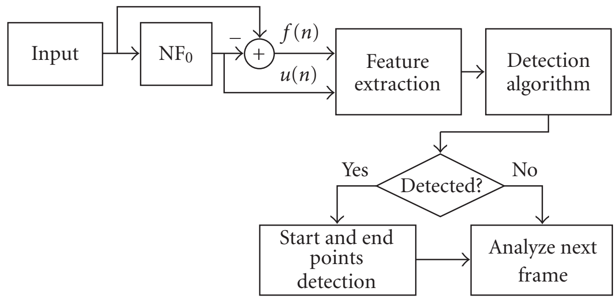

FIGURE 1: Block diagram of the detection technique of abnormal conditions.

To go into detail of the proposed technique, Section 3.1 describes the scheme for detecting disturbances. In sequel, Section 3.2 details the notch filter. Thereafter, Section 3.3 briefly highlights higher-order statistics and the feature selection technique. Finally, Section 3.4 addresses the detection algorithm.

3.1. Scheme of proposed technique

The block diagram of the proposed technique for detecting abnormal conditions in voltage signal is depicted in Figure 1. The main blocks in this figure are detailed as follows.

(1) *Input*: this block provides the N-length input vector $\mathbf{x}$ in which the elements are given by (1).

(2) *Notch filter*: this block implements a second-order notch filter in which the notch frequency is $\omega_0 = 2\pi(f_0/f_s)$. The main advantage regarding the use of such approach is that a finite-length implementation of such filter with at least 10 bits is enough to reproduce an approximated infinite precision notch filter response if $f_0 \ll f_s$ [26, 27].

(3) *Feature extraction*: in this block, the selected HOS-based features named cumulants of second- and fourth-order are extracted from the vectors $\mathbf{f}$ and $\mathbf{u}$ to reveal in a simple way abnormal behaviors in vector $\mathbf{x}$.

(4) *Detection algorithm*: in this block Bayes detection rule based on the *maximum likelihood* (ML) criterion is applied [20, 21, 28]. The probability density function is the Gaussian or normal density function. The major reasons for the normal density function use is its computational tractability and the fact that it modeled very well this detection problem. Additionally, if there is linear separability among the regions associated with the normal and abnormal conditions in the vector space of extracted parameters, then linear technique that efficiently detects the occurrence of disturbances

is implemented. The parameters of the linear technique can be adaptively obtained by using the *least mean square* (LMS) or the *recursive least square* (RLS) algorithm [29].

(5) *Start and end point detection*: in this block a simple procedure, which is capable of informing the start and end points of a detected abnormal condition in the vector $\mathbf{x}$, is implemented. The procedure is as follows.

Step 1. Vectors $\mathbf{f}(n-L_f) = [f(n-L_f)\cdots f(n-L_f(i+1)+1)]^T$ and $\mathbf{u}(n-iL_u) = [u(n-iL_u)\cdots u(n-L_u(i+1)+1)]^T$ are, respectively, composed of samples from $\mathbf{f}$ and $\mathbf{u}$ vectors, whose samples are inputs of the feature extraction block. Note that L_f and L_u are lengths of vectors $\mathbf{f}(n-iL_f)$ and $\mathbf{u}(n-iL_u)$, respectively, and $i = 0, 1, 2, 3, \ldots$.

Step 2. HOS-based features are extracted from $\mathbf{f}(n-iL_f)$ and $\mathbf{u}(n-iL_u)$ sequences.

Step 3. The start point of an abnormal event is given by

$$k = \min\left[iL_f, iL_u\right], \tag{15}$$

where iL_f and iL_u refer to the vectors $\mathbf{f}(n-iL_f)$ and $\mathbf{u}(n-iL_u)$ from which the differences between their HOS-based features and the HOS-based features extracted from the previous vectors are greater than a specified threshold.

Step 4. The end point of an abnormal event is given by

$$j = \max\left[iL_f, iL_u\right], \quad i \geq k, \tag{16}$$

where iL_f and iL_u are the end points detected in the $\mathbf{f}(n-iL_f)$ and $\mathbf{u}(n-iL_u)$ vectors from which the differences between their HOS-based features and the HOS-based features extracted from the previous vectors are greater than a specified threshold.

One can note that $L_f \gg L_u$ because the abnormal events related to the fundamental component are slower than the ones that occur in the error signal component.

(6) *Analyze next frame*: this block is responsible for acquiring the next frame for detection purpose.

3.2. Notch filter structure

The z-transform of a second-order notch filter, whose notch frequency is $\omega_0 = 2\pi(f_0/f_s)$, is expressed by

$$H_0(z) = \frac{1 + a_0 z^{-1} + z^{-2}}{1 + \rho_0 a_0 z^{-1} + \rho_0^2 z^{-2}}, \tag{17}$$

where

$$a_0 = -2\cos\omega_0 \tag{18}$$

and $0 \ll \rho_0 < 1$ is the notch factor.

The feature extraction is performed over the notch filter output $u(n)$ and from the signal $f(n)$, which is obtained by the subtraction of $u(n)$ from the input signal $x(n)$. The implementation of notch filter in the δ operator domain is given by [26, 27],

$$H_0(\delta) = H_0(z)|_{z=1+\Delta\delta} = \frac{1 + \alpha_{0,1}\delta^{-1} + \alpha_{0,2}\delta^{-2}}{1 + \beta_{0,1}\delta^{-1} + \beta_{0,2}\delta^{-2}}, \tag{19}$$

where

$$\begin{aligned}
\alpha_{0,1} &= \frac{2}{\Delta}\left(1 - \cos\omega_0\right),\\
\alpha_{0,2} &= \frac{2}{\Delta^2}\left(1 - \cos\omega_0\right),\\
\beta_{0,1} &= \frac{2}{\Delta}\left(1 - \rho_0\cos\omega_0\right),\\
\beta_{0,2} &= \frac{1 + \rho_0^2 - 2\rho_0\cos\omega_0}{\Delta^2}.
\end{aligned} \tag{20}$$

Even though $\Delta \in [0, \infty)$, usually the value of it is very small, $0 < \Delta \ll 1$, and carefully chosen for diminishing *roundoff* error effects. Although the implementation of a filter in the δ operator domain demands more computational complexity, it is very robust to quantization effects.

3.3. High-order statistics

Some contributions have demonstrated that HOS-based techniques are more appropriate to deal with non-Gaussian processes and nonlinear systems than second-order-based ones. Remarkable results regarding detection, classification and system identification with cumulant-based technique have been reported in [16, 17, 22, 23, 25]. Assuming that components $\mathbf{f}$ and $\mathbf{u}$ of voltage signals are modeled as a non-Gaussian process, the use of cumulant-based technique appears to be a very promising approach for detection of abnormal behaviors in voltage signals.

The expressions of the diagonal slice of second-, third-, and fourth-order cumulants of a zero mean vector $\mathbf{z}$, which is assumed to be $\mathbf{f} - E\{\mathbf{f}\}$ and $\mathbf{u} - E\{\mathbf{u}\}$, where $E\{\cdot\}$ is the expectation operator, are expressed by

$$\begin{aligned}
c_{2,z}(i) &= E\{z(n)z(n+i)\},\\
c_{3,z}(i) &= E\{z(n)z^2(n+i)\},\\
c_{4,z}(i) &= E\{z(n)z^3(n+i)\} - 3c_{2,z}(i)c_{2,z}(0),
\end{aligned} \tag{21}$$

respectively, where i is the ith lag. Considering $\mathbf{z}$ as a finite-length vector and $i = 0, 1, 2, \ldots, N-1$, approximations of such cumulants are here, for the first time, defined by

$$\begin{aligned}
\tilde{c}_{2,z}(i) &:= \frac{1}{N}\sum_{n=0}^{N-1} z(n)z[\mathrm{mod}(n+i, N)],\\
\tilde{c}_{3,z}(i) &:= \frac{1}{N}\sum_{n=0}^{N-1} z(n)z^2[\mathrm{mod}(n+i, N)],\\
\tilde{c}_{4,z}(i) &:= \frac{1}{N}\sum_{n=0}^{N-1} z(n)z^3[\mathrm{mod}(n+i, N)]\\
&\quad - \frac{3}{N^2}\sum_{n=0}^{N-1} z(n)z[\mathrm{mod}(n+i, N)]\sum_{n=0}^{N-1} z^2(n),
\end{aligned} \tag{22}$$

where $\mathrm{mod}(a, b)$ is the modulus operator, which is defined as the remainder obtained from dividing a by b. The approximations presented in (22) lead to a very appealing approach for problems where one has a finite-length vector from which higher-order-based features have to be extracted for applications, such as detection, classification, and identification. One has to note that the use of mod$(\cdot)$ operator means that we are considering that the vector $\mathbf{z}$ is an N-length periodic vector. The reason for this refers to the fact that by using such very simple assumption, we can evaluate the approximation of HOS with all available N samples. As a result, the extracted feature vector is more representative than the feature vector extracted with a standard approximation of HOS given by

$$\begin{aligned}\hat{c}_{2,z}(i) &= \frac{2}{N}\sum_{n=0}^{N/2-1} z(n)z(n+i),\\ \hat{c}_{3,z}(i) &= \frac{2}{N}\sum_{n=0}^{N/2-1} z(n)z^2(n+i),\\ \hat{c}_{4,z}(i) &= \frac{2}{N}\sum_{n=0}^{N/2-1} z(n)z^3(n+i)\\ &\quad - \frac{12}{N^2}\sum_{n=0}^{N/2-1} z(n)z(n+i)\sum_{n=0}^{N/2-1} z^2(n),\end{aligned} \tag{23}$$

where $i = 0, \ldots, N/2-1$.

Once the cumulants have been extracted, many different processing techniques can be applied on HOS-based features before their use for detection purpose. The motivation for using different approaches for postprocessing the extracted HOS-based features resides on the fact that they facilitate the detection process of abnormal conditions. Note that this is a heuristic approach that emerged as a result of a careful analysis of the HOS-based features extracted from many voltage signals. Although it is a heuristic approach, it is worth stating that to detect a disturbance what make difference is if the set of features facilitates or not the detection process.

The HOS-based feature vector extracted from the vector $\mathbf{z}$, in which the elements are candidates for use in the proposed technique, is given by

$$\mathbf{p}_i = \left[\bar{\mathbf{c}}_{2,f}^T \bar{\mathbf{c}}_{3,f}^T \bar{\mathbf{c}}_{4,f}^T \bar{\mathbf{c}}_{2,u}^T \bar{\mathbf{c}}_{3,u}^T \bar{\mathbf{c}}_{4,u}^T\right]^T, \quad i = 1, 2, \tag{24}$$

where $\bar{\mathbf{c}}_{2,z} = [\tilde{c}_{2,z}(0) \cdots \tilde{c}_{2,z}(N-1)\hat{c}_{2,z}(0) \cdots \hat{c}_{2,z}(N/2-1)]^T$, $\bar{\mathbf{c}}_{3,z} = [\tilde{c}_{3,z}(0) \cdots \tilde{c}_{3,z}(N-1)\hat{c}_{3,z}(0) \cdots \hat{c}_{3,z}(N/2-1)]^T$, and $\bar{\mathbf{c}}_{4,z} = [\tilde{c}_{4,z}(0) \cdots \tilde{c}_{4,z}(N-1)\hat{c}_{4,z}(0) \cdots \hat{c}_{4,z}(N/2-1)]^T$. $\mathbf{z}$ denotes $\mathbf{f}$ and $\mathbf{u}$. In (24), $i = 1$ and $i = 2$ denote normal and abnormal conditions in the vector $\mathbf{x}$.

Aiming at the choice of a representative and finite set of features from (24) that provides a good separability between two distinct conditions that are individually represented by hypotheses $\mathcal{H}_0$ and $\mathcal{H}_1$, and hypotheses $\mathcal{H}_2$ and $\mathcal{H}_3$, as seen in (14), the use of the *Fisher discriminant ratio* (FDR) is applied [28]. The cost vector function of the FDR which leads to the best separability in a low-dimensional space between both aforementioned events, is given by

$$\mathbf{J}_c = (\mathbf{m}_1 - \mathbf{m}_2)^2 \odot \frac{1}{\mathbf{D}_1^2 + \mathbf{D}_2^2}, \tag{25}$$

where $\mathbf{J}_c = [J_1 \cdots J_{L_l}]^T$, L_l is the total number of features, $\mathbf{m}_1$ and $\mathbf{m}_2$, and $\mathbf{D}_1^2$ and $\mathbf{D}_2^2$ are the means and variances vectors of features vectors $\mathbf{p}_{1,k}, k = 1, 2, \ldots, M_p$ and $\mathbf{p}_{2,k}, k = 1, 2, \ldots, M_p$. M_p denotes the total number of feature vectors. The symbol $\odot$ refers to the Hadarmard product $\mathbf{r} \odot \mathbf{s} = [r_0 s_0 \cdots r_{L_r-1} s_{L_r-1}]^T$.

The ith element of the parameter vector, see (25), having the highest value, $\mathbf{J}_c(i)$, is selected for use in the detection technique. Applying this procedure to all elements of the feature vector, the K parameters associated with the K highest values of $\mathbf{J_c}$ are selected.

3.4. Detection techniques

From the hypotheses stated in (14), the detection problem can be viewed as a classification problem, where hypotheses $\mathcal{H}_0$ and $\mathcal{H}_1$ refer to a classification region $\mathcal{R}_n = \mathcal{R}_0 \bigcup \mathcal{R}_1$ associated with the normal operation of voltage signal, while hypotheses $\mathcal{H}_2$ and $\mathcal{H}_3$ are related to classification region $\mathcal{R}_a = \mathcal{R}_2 \bigcup \mathcal{R}_3$ which refers to abnormal condition. From the above point of view, numerous classification techniques can be applied to determine the hyperplane or nonlinear curves that separate region $\mathcal{R}_n$ from region $\mathcal{R}_a$, see [30].

By considering this paradigm, the goal is the choice of well-suited classification techniques which lead to a good trade-off between performance and computational complexity if $N = 256, 128, 64, 32$, and 16. By considering the conditional probabilities as a Gaussian ones and assuming that the Gaussian parameters are estimated from the training data, then the likelihood ratio test of the *maximum likelihood* (ML) criterion is given by

$$\frac{p_{\mathbf{x}|\mathcal{H}_0,\mathcal{H}_1}(\mathbf{x} \mid \mathcal{H}_0, \mathcal{H}_1)}{p_{\mathbf{x}|\mathcal{H}_2,\mathcal{H}_3}(\mathbf{x} \mid \mathcal{H}_2, \mathcal{H}_3)} \underset{<}{\geq} \frac{\pi_0}{\pi_1}, \tag{26}$$

where $\pi_0 = 1/2$ and $\pi_1 = 1/2$ are the a priori probabilities of normal and abnormal conditions associated with the voltage signals.

4. NUMERICAL RESULTS

In this section, the performance of the proposed technique is evaluated to validate its effectiveness for detecting disturbances in voltage signals. In addition, in this section, comparison results between the proposed technique and the technique introduced in [3] is presented.

To evaluate the performance of the proposed technique, several waveform of voltage signals were synthetically generated. The generated disturbances are sags, swells, interruptions, harmonics, damped oscillations, notches, and spikes. The sampling rate considered was $f_s = 256 \times 60$ *samples per second* (sps). Simulation with other sampling rates was performed, but will not be presented here for the sake of simplicity. However, it is worth mentioning that similar performance of the proposed technique is verified when $f_s = 32{\times}60$ Hz, $f_s = 64{\times}60$ Hz, $f_s = 128{\times}60$ Hz, $f_s = 512{\times}60$ Hz, $f_s = 1024 \times 60$, and $f_s = 2048 \times 60$ Hz if we take into account $N \geq 16$. For the notch filter, $\rho_0 = 0.997$.

Also, the detection performance of the proposed technique is verified with measurement data of voltage signals available from IEEE working group P1159.3 website, which focused on data file format for power quality data

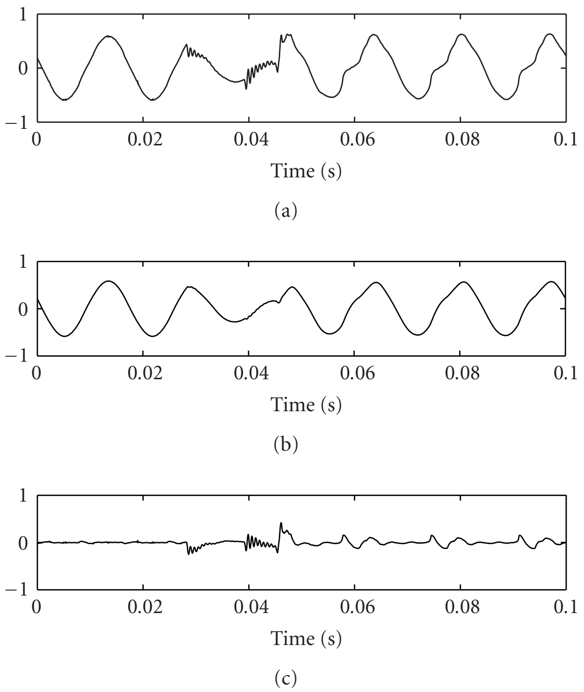

Figure 2: (a) Signal $\{x(n)\}$, (b) signal $\{f(n)\}$, (c) signal $\{u(n)\}$.

interchange. The available voltage measurement were obtained with $f_s = 256 \times 60$ Hz. The SNR of these data was estimated to be 40 dB.

For the sake of simplicity, the proposed technique is named HOS, the techniques introduced in [3] are named RMS 1 and RMS 2. RMS 1 and RMS 2 refer to the detection techniques based on the rms evaluation with a half and one cycles of the fundamental component, respectively.

An illustrative example of a voltage signal obtained from IEEE working group P1159.3 website and considered in this section is depicted in Figure 2. It is seen from Figure 2(a) the voltage signal expressed by (1), Figure 2(b) shows the extracted fundamental component added with some kind of variation represented by $\{\Delta f_{ss}(n)\}$, and Figure 2(c) depicts the transient component of the voltage signal. From the result obtained, it can be noted that not only the transient signal carry out relevant information but also the fundamental component. This is the reason why the proposed technique makes use of information from both components for detection purpose.

Figures 3–7 show the HOS-based features selected with the FDR criterion. One has to note these pictures portray the extracted features when the notch filter and ideal notch filter are used to decompose the vector $\mathbf{x}$ into vectors $\mathbf{f}$ and $\mathbf{u}$. The comparison between the attained results with the notch and ideal filters shows that the second-order notch filter can be used to approximate the ideal notch filter without significant loss of performance. Analyzing Figures 3–5, it is seen that two, $K = 2$, HOS-based features are enough for detecting abnormal condition in voltage signals when $N = 256, 128$, and 64. For frame lengths equal to $N = 32$ and 16, at least,

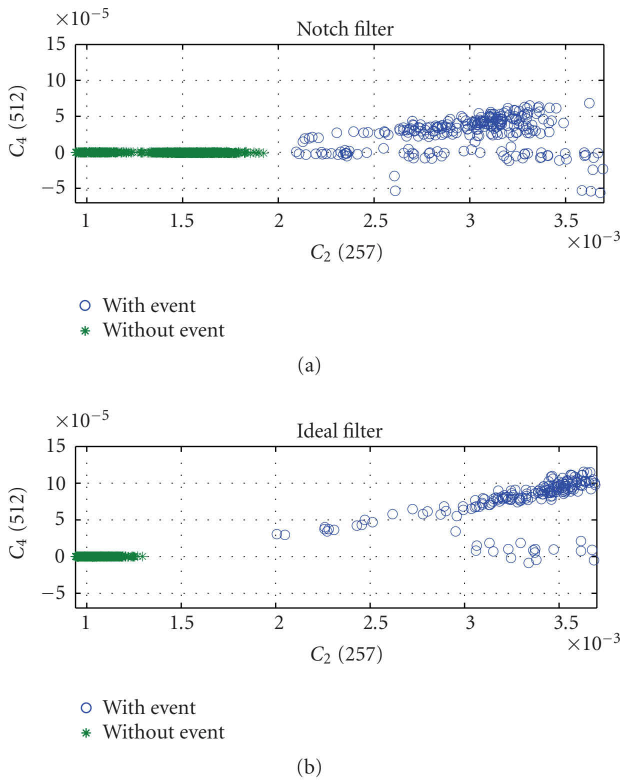

Figure 3: HOS-based features extracted from voltage signals whose frame length is equal to $N = 256$. For this frame length, second- and fourth-order statistics are extracted from $\mathbf{u}$.

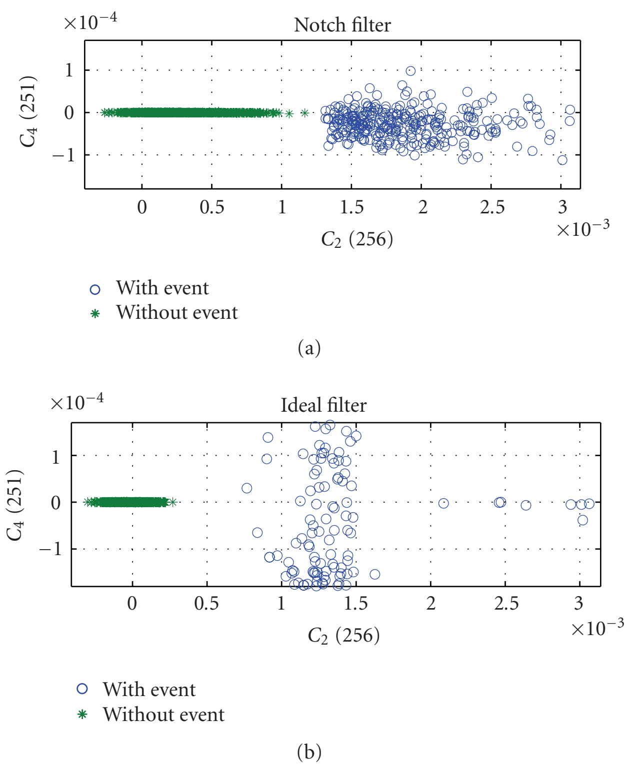

Figure 4: HOS-based features extracted from voltage signals whose frame length is equal to $N = 128$. For this frame length, second- and fourth-order statistics are extracted from $\mathbf{u}$.

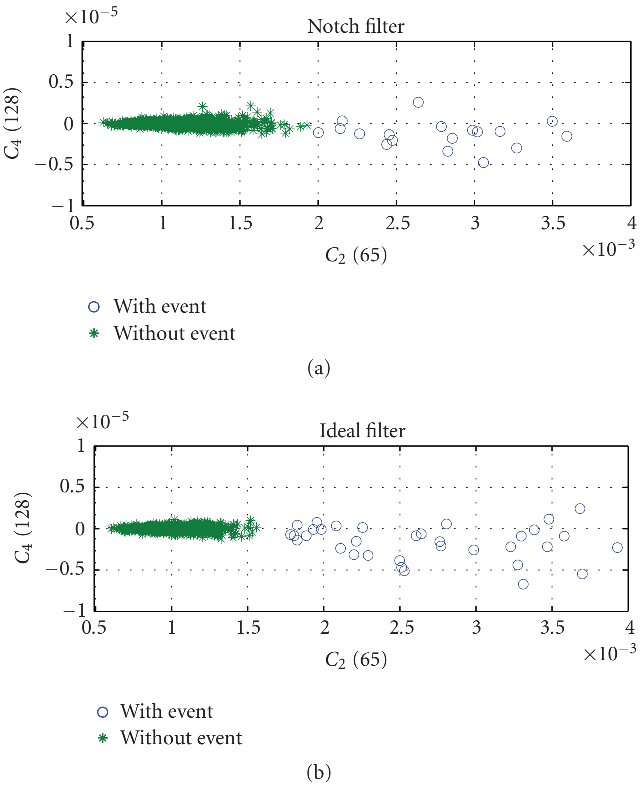

Figure 5: HOS-based features extracted from voltage signals whose frame length is equal to $N = 64$. While second-order statistics are extracted from $\mathbf{f}$, the fourth-order statistic is extracted from $\mathbf{u}$.

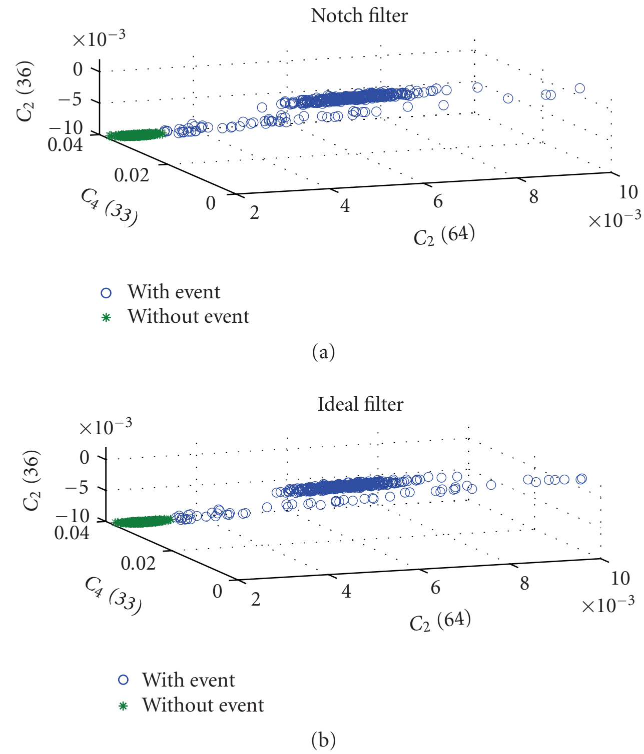

Figure 6: HOS-based features extracted from voltage signals whose frame length is equal to $N = 32$. While second-order statistics are extracted from $\mathbf{f}$, the fourth-order statistic is extracted from $\mathbf{u}$.

three, $K = 3$, features are needed, see Figures 6-7. These results were obtained with the discussed procedure for feature extraction and selection applied to many voltage signals. The voltage signals analyzed comprise typical waveform voltage disturbances.

Figure 8 gives a picture of the performance of the HOS, RMS 1, and RMS 2 techniques when $f_s = 256 \times 60$ Hz and $N = 256, 128, 64, 32$, and 16. These used frame lengths correspond to 1, 1/2, 1/4, 1/8, and 1/16 cycles of the fundamental component, respectively. To obtain these results, 2236 synthetic waveforms of voltage signals were generated. The synthetic voltage disturbances generated are sags, swells, interruptions, harmonics, damped oscillations, notches, and spikes. Although in measurement data we can see that the SNR is around 40 dB, we evaluated the performance of the three detection techniques for the SNR ranging from 5 up to 30 dB, but, for the sake of simplicity, only the results achieved when SNR = 30 dB are presented. From this plot, one can see that HOS technique performance provides the lowest error detection rate.

Figure 9 shows the results achieved when sags, swells, and interruptions occur in the voltage signals to illustrate the performance of all techniques when typical disturbances associated with the fundamental components occur. The frame lengths correspond to 1, 1/2, 1/4, 1/8, and 1/16 cycles of the fundamental component and the number of synthetic waveform is equal to 880. One can note that the performance difference among HOS, RMS 1, and RMS 2 techniques is

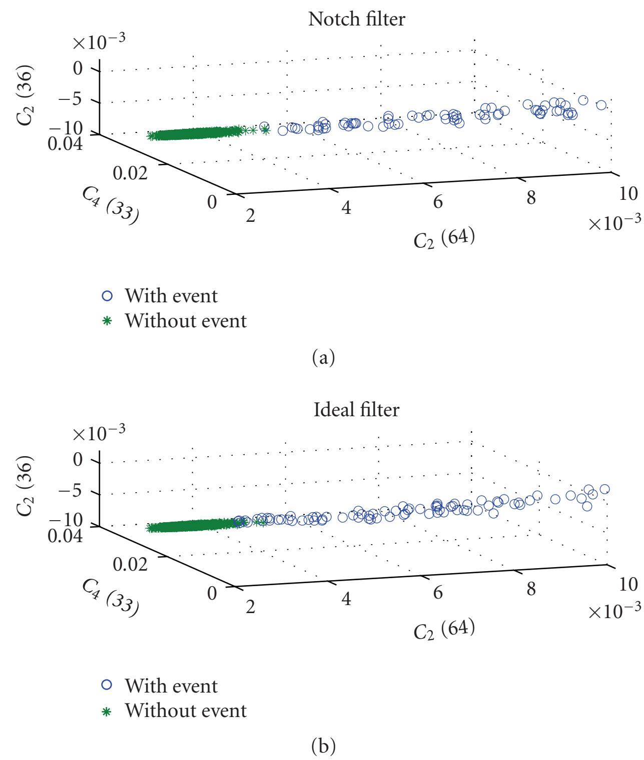

Figure 7: HOS-based features extracted from voltage signals whose frame length is equal to $N = 16$. While second-order statistics are extracted from $\mathbf{f}$, the fourth-order statistic is extracted from $\mathbf{u}$.

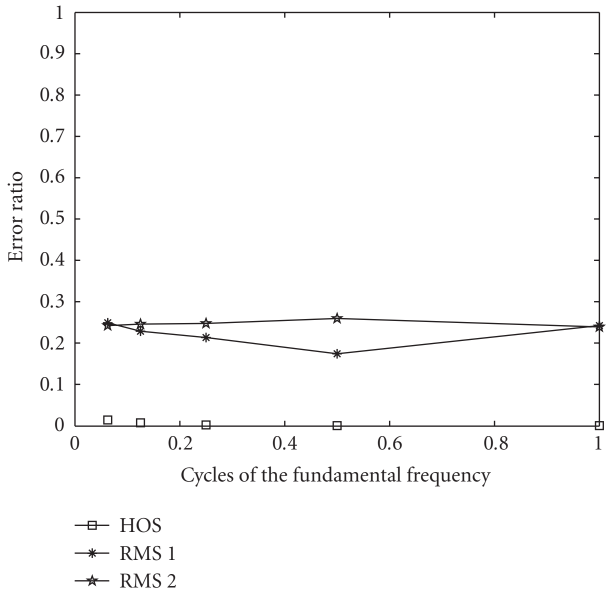

Figure 8: Error detection rate when the frame lengths correspond to 1/16, 1/8, 1/4, 1/2, and 1 cycles of the fundamental component.

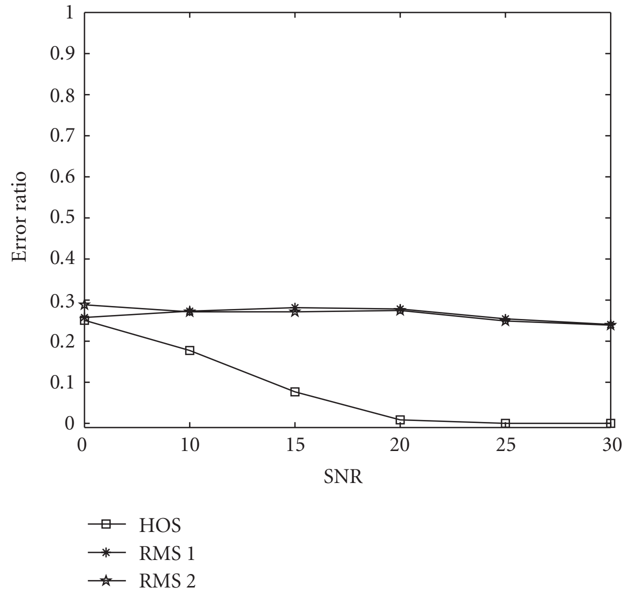

Figure 10: Error detection rate when the frame length is equal to one cycle of the fundamental component and the SNR ranges from 5 up to 30 dB.

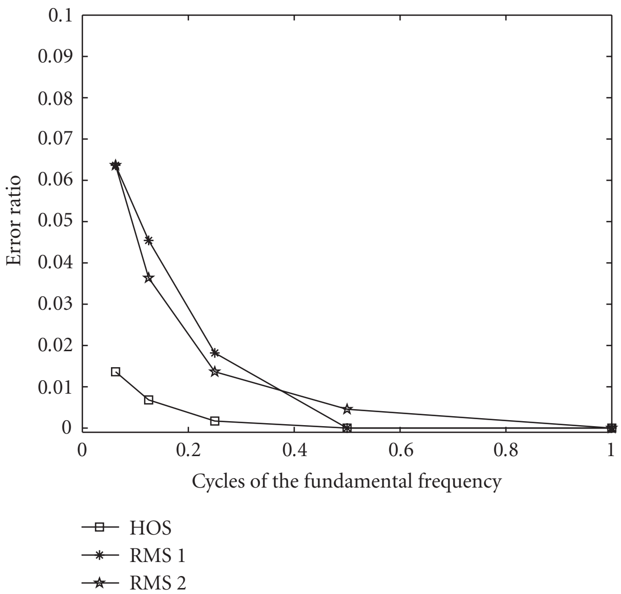

Figure 9: Error detection rate when the frame lengths are 1/16, 1/8, 1/4, 1/2, and 1 cycles of the fundamental component.

considerably reduced. It is something expected because RMS 1 and RMS 2 techniques were developed to detect sag disturbances as well as their sources. Based on other simulation results, one can state that if the disturbance set is reduced to be composed of voltage sags, then the performance of the HOS technique is slightly better than the performance of RMS 1 and RMS 2 techniques if SNR is higher than 25 dB and much better if the SNR is lower than 25 dB. From the results portrayed in Figures 8 and 9, one can note that the proposed technique offers a considerable enhancement compared with the previous ones. In fact, the use of information from both fundamental and transient components provides more relevant characterization of disturbances in voltage signals, especially when N is reduced.

The results obtained with HOS, RMS 1, and RMS 2 techniques when the SNR varies between 5 and 30 dB is highlighted in Figure 10. The following considerations were taken into account to carry out the simulation: (i) the frame length is equal to one cycle of the fundamental component, (ii) $f_s = 256 \times 60$ Hz, (iii) the generated synthetic voltage disturbances are sags, swells, interruptions, harmonics, damped oscillations, notches, and spikes, (iv) the number of data is 2236. The results verify that HOS technique presents an improved performance when the SNR is higher than 10 dB.

Figure 11 shows the performance of all three detection techniques when the measurement data of the IEEE working group P1159.3 are used. This database is comprised of isolated and multiple events. The HOS, RMS 1, and RMS 2 techniques were designed with real data in which the SNR is equal 40 dB. The generated voltage disturbances are sags, swells, interruptions, harmonics, damped oscillations, notches, and spikes. And, the numbers of data for design and test are equal to 2236 and 110, respectively. It is clear to note that the HOS technique is capable of detecting all disturbances, but the same is not possible with the RMS 1 and RMS 2 techniques.

The performance of the HOS technique when the SNR ranges from 5 up to 30 dB and the frame lengths correspond to 1, 1/2, 1/4, 1/8, and 1/16 cycles of the fundamental component is depicted in Figure 12. One can note that the performance of the HOS-based technique achieves expressive detection rate when the SNR is higher than 25 dB.

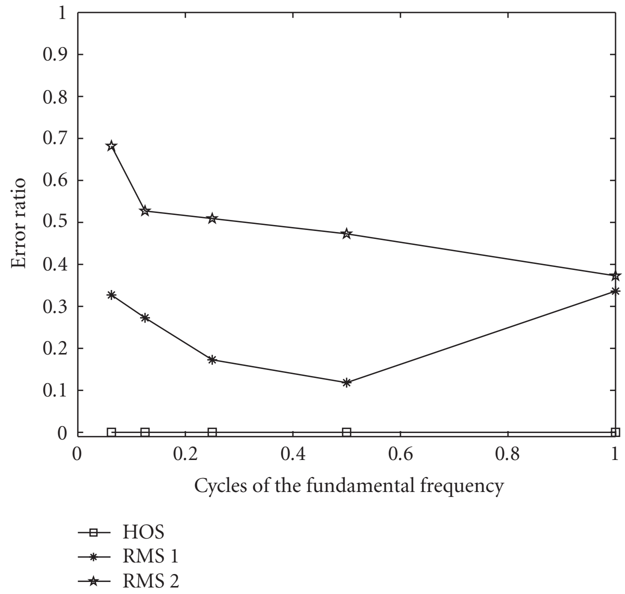

FIGURE 11: Error detection rate when the measurement data from IEEE working group P1159.3 is considered. The frame lengths are equal to 1/16, 1/8, 1/4, 1/2, and 1 cycles of the fundamental component and the SNR is around 40 dB.

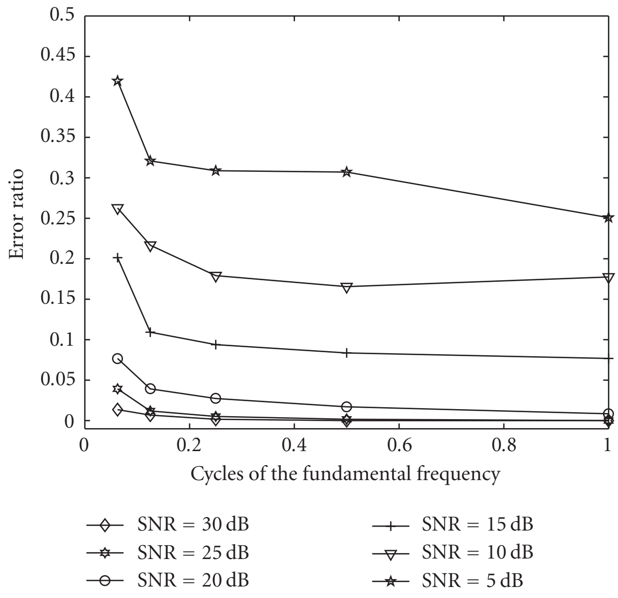

FIGURE 12: Error detection rate attained by HOS when the frame length is equal to 1/16, 1/8, 1/4, 1/2, and 1 cycles of the fundamental component and the SNR ranges from 5 up to 30 dB.

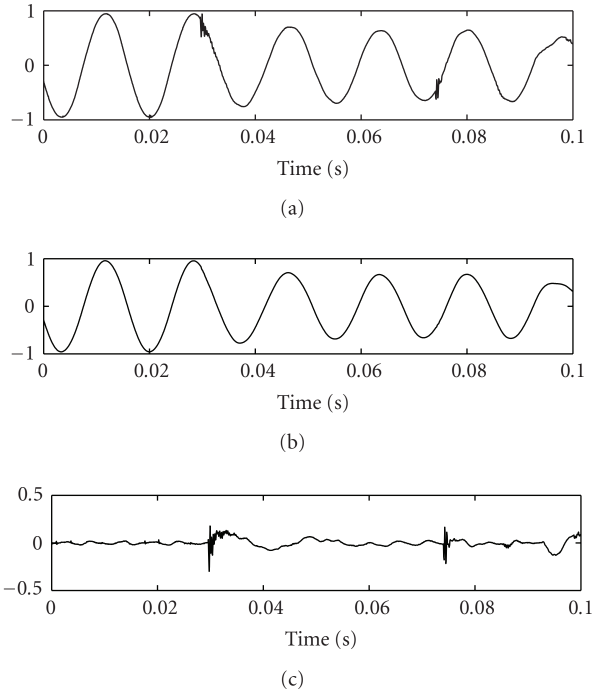

FIGURE 13: (a) Signal $\{x(n)\}$, (b) signal $\{f(n)\}$, (c) signal $\{u(n)\}$.

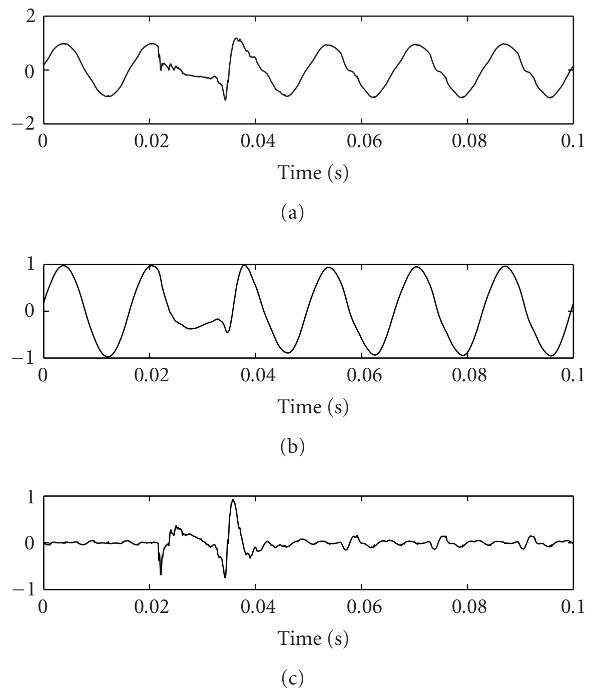

FIGURE 14: (a) Signal $\{x(n)\}$, (b) signal $\{f(n)\}$, (c) signal $\{u(n)\}$.

Overall, from the results obtained, it is seen that the proposed technique is more effective in terms of performance than the technique introduced in [3], if a reduced-length vector $\mathbf{x}$ is considered for detecting abnormal conditions of voltage signals.

Now, in order to present the behavior of the proposed technique to pinpoint, the start and end points of disturbances in voltage signals, Figures 13 and 14 show real voltage signals obtained from IEEE working group P1159.3 website, $\{x(n)\}$, and their corresponding $\{f(n)\}$ and $\{u(n)\}$ components, which are extracted in accordance to the proposed technique, and Figures 15 and 16 depict the extracted HOS-based parameter from these signals. $L_N = 128$ for $\{x(n)\}$ and $\{f(n)\}$ signals and $L_N = 8$ for $\{u(n)\}$ signals. The

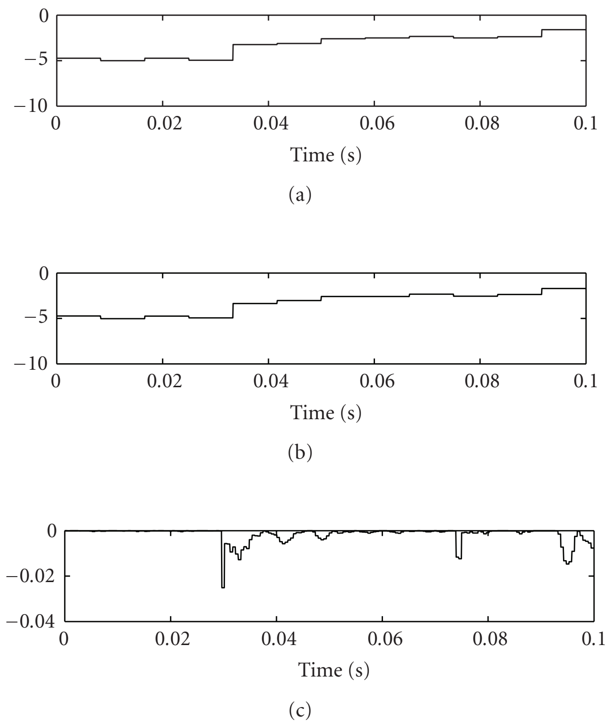

FIGURE 15: (a) $C_4(0)$ HOS-based parameter extracted from $\{x(n)\}$, (b) $C_4(0)$ HOS-based parameter extracted from $\{f(n)\}$, (c) $C_4(0)$ HOS-based parameter extracted from $\{u(n)\}$.

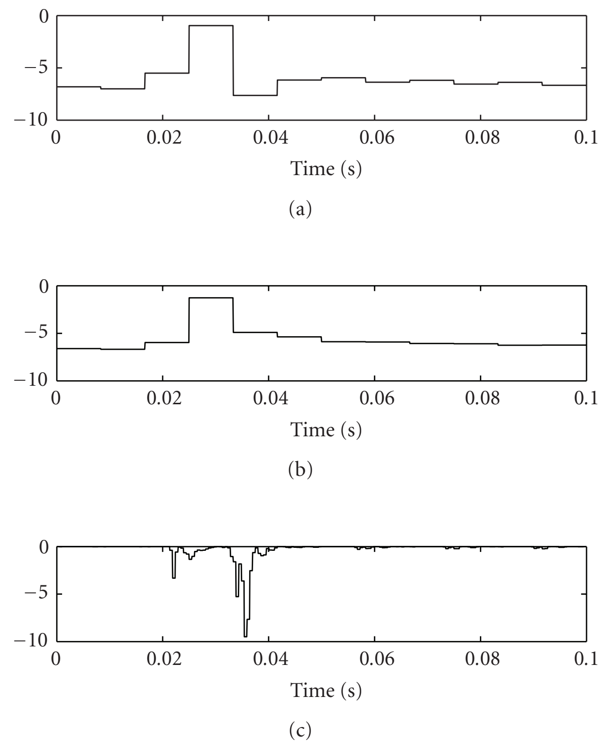

FIGURE 16: (a) $C_4(0)$ HOS-based parameter extracted from $\{x(n)\}$, (b) $C_4(0)$ HOS-based parameter extracted from $\{f(n)\}$, (c) $C_4(0)$ HOS-based parameter extracted from $\{u(n)\}$.

reason for using fourth-order cumulants instead of second- or third-order cumulants resides on the fact the former revealed through simulations to be more appropriate than the latter. Note that the start and end points of the abnormal event can be very well detected with features based on fourth-order cumulants.

5. CONCLUSIONS

A disturbance detection technique for voltage signals has been introduced. The proposed technique allows the detection of abnormal conditions in frame with at least $N = 16$ elements. Although, we have presented results based on voltage signals sampled at $f_s = 256 \times 60$ Hz, we have verified that the same behavior is attained if the sampling rate is reduced or increased. This feature is a very attractive one because the detection of abnormal voltage signals can be performed at frames which correspond to multiple or submultiples of one-cycle fundamental component when different sampling rates are considered. As a result, occurrences of short- and long-time voltage disturbances can be detected appropriately.

From the results reported in Section 4, one can note that the proposed technique, which was designed to detect the occurrence and the start and end point of events in voltage signals, can be applied not only for power quality application but also to digital protection of power system that demands fast, efficient, and simple detection techniques.

Future works are toward the development of signal processing techniques capable of decomposing the power line signals with reduced transient effect, the investigation of the proposed HOS-based technique to digital protection of power system and its extension to three-phase case.

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